Building a Competitive Roster: The Impact of Salary Inequality on NBA Team Performance

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This study explores whether paying National Basketball Association, NBA, stars disproportionately more than their teammates improves team performance. This study constructs a balanced panel of all 30 franchises over the 2017–2023 seasons (210 team-years) by merging Spotrac salary data (Spotrac, 2025) with Basketball-Reference (Basketball Reference, 2025) performance statistics. Payroll inequality among active players is captured by an Active Gini coefficient that ranges from 0 (equal pay) to 1 (one player earns all active salary). Team success is measured by a Composite Score, the product of adjusted net rating and team-summed VORP, rescaled from 0 (historically bad) to 1 (historically elite). Ordinary least squares with team fixed effects indicates that a 10% rise in Active Gini lifts Composite Score by 0.035 points, roughly the gap between a play-in team and a secure playoff seed. Inequality tied to inactive or injured contracts moves performance in the opposite direction. To address reverse causality, Active Gini coefficient is instrumented with lagged salary-cap level and lagged payroll; two-stage least squares yields a larger causal estimate of 0.09. Nonlinear specifications suggest no meaningful inverted-U relationship, though instruments for higher-order terms are weak. Overall, the evidence supports tournament-style incentives: higher spending on active stars boosts outcomes, compared to dollars tied up in injuries or non-playing contracts undermine them. These findings give front offices clear, quantitatively grounded guidance on how to allocate payroll for competitive success.

Introduction

In recent years, NBA front offices have increasingly concentrated team payroll in the hands of a few star players. Rather than distributing salaries evenly across the roster, many franchises, especially contenders, build around two or three max-contract players and rely on minimum deals or rookie contracts to fill out the bench. This "stars and depth" tradeoff has become central to modern roster construction, shaping cap strategy, trade policy, and long-term team planning. The Collective Bargaining Agreement (NBA & NBPA, 2017), along with the introduction of two-way contracts, has reinforced this trend by allowing teams to fill out regular-season depth at low cost using players who split time between the NBA and its development league, the G-League.

Roster decisions are not purely financial. They reflect strategic uncertainty about how salary structure affects team dynamics and on-court performance. Prioritizing star players can align compensation with impact, ensuring that those with the largest roles are rewarded accordingly. On the other hand, sharp pay disparities may generate frustration among role players, particularly in a sport where trust, cohesion, and effort allocation are incredibly complex and intertwined. General managers or those in charge of player personnel decisions must make decision regarding these tradeoffs, often without clear empirical support.

This paper examines how intra-team salary inequality relates to team performance across the modern NBA landscape. While prior research in sports economics has explored inequality-performance relationships, most studies rely on win percentage as the outcome variable and fail to distinguish between different salary types. This misses critical context: in practice, teams pay for production, not for contracts associated with players who are waived (dead money), retained, suspended, or held for future rights.
To address these issues, this study introduces two key innovations and compare them to previous approaches. First, Active Gini is used, a Gini coefficient calculated solely from the cash shares of players currently active on the roster. The Gini coefficient is a widely used measure of inequality that ranges from 0 (perfect equality) to 1 (maximum inequality), making it a well applied measurement to compare payroll dispersion across teams and seasons. Active Gini more accurately reflects the pay structure relevant to performance and in-game dynamics. This improves upon traditional measures that include all salary obligations, even for players who no longer contribute on the court. It focuses attention on the portion of contracts most likely to influence chemistry, effort, and production.

Constructing a more informative outcome variable: the Composite Score, defined as the product of min-max scaled Adjusted Net Rating and team-summed VORP. This normalized measure captures both team-level efficiency and cumulative player value, aligning more closely with how NBA decision-makers evaluate success. It recognizes that performance is a function of both skill and execution, and provides a richer picture than win percentage alone, which offers no insight into margin of victory, opponent strength, or pace.

These empirical choices reflect the practical goals of NBA teams. Front offices aim to win games, but they must do so by constructing rosters that balance on-court performance with financial and structural constraints. Their objective is to assemble cost-efficient, high-performing teams that maximize output within the limits of the soft salary cap of the NBA. A player earning $40 million while missing 50 games affects performance very differently than a similarly paid player who logs heavy minutes. Additionally, inflated payrolls driven by dead, retained, or otherwise inactive contracts fail to reflect current productivity.

By focusing on active contributors, performance-sensitive outcomes, and econometric methods including instrumental variables and interaction terms, this paper offers a more nuanced framework for evaluating how salary inequality influences team success. Rather than asking whether inequality is inherently good or bad: what kind of inequality matters, under what conditions, and for which players?

Background

Theoretical Foundations: Pay Dispersion and Team Performance

Tournament Incentives: Lazear and Rosen (1981) formalize the idea that large pay spreads can boost individual effort by offering a substantial "prize" to top performers. In the NBA, the prize is not only status but also the potential of future maximum contracts, endorsement deals, and a leading on court role. A steep internal salary distribution could improve offseason preparation and in-game intensity. When a roster has clear talent rankings, players know what is required to climb the ladder. Tournament theory predicts a positive linear relationship between pay inequality and output, more inequality incentivizes higher performance, at least up to the point where physical limits or strategic constraints cap what a team can achieve.

Fairness and Cohesion: Not all effects of inequality are positive. Levine (1991), building on social-comparison research, argues that wide pay gaps can create envy, erode trust, and weaken communication within groups. Akerlof and Yellen (1990) give this intuition formal shape in a fair-wage–effort model: workers who feel underpaid relative to a reference group will retain effort. In basketball, trust and cohesion are vital for coordinated defense, unselfish passing, and overall team chemistry. Given the high stakes, even a small drop in team unity could erode team performance. This perspective predicts that excessive within team inequality may hurt outcomes as underpaid players motivation suffers or become less cooperative.

Principal–Agent Problems: A third theory involves incentives over time. Stiroh (2007) documents that NBA players tend to improve their performance in the final year of a contract and often decline once a long-term deal is secured. This pattern is a moral hazard issue: guaranteed money weakens the link between current effort and future earnings. Consequently, a roster loaded with high-paid veterans on long contracts may suffer complacency, compared to a roster of underpaid players on short "prove-it" deals might show extra effort relative to pay. In principal–agent terms, inequality stemming in long-term contracts can hurt team output if star players coast, while inequality stemming from short-term contracts can boost output if role players exceed expectations.

Balancing Incentives and Cohesion: In theory, the forces above work in against another, implying a trade-off that is likely non-linear. A moderate pay gap may create an optimal balance, extracting the motivational benefits of a tournament while avoiding the morale costs of perceived unfairness. Comparatively, extremely egalitarian rosters could lack competitive spark, and extremely unequal rosters could suffer internal conflict or complacency. This reasoning leads one to expect an inverted-U relationship between pay dispersion and team performance. In other words, some inequality may be better than none, but beyond a point the negative effects of pay inequality may outweigh the positive effects.

Empirical Evidence from Other Sports and the NBA

Evidence from European Soccer: Studies in other sports have tested these theoretical predictions. Franck and Nüesch (2011), find that team performance initially rises as the Gini coefficient increases from a very egalitarian roster to a moderately unequal one, then dips at mid-level inequality, and finally rises again for highly star-dominated squads. They explain this second uptick by noting that a single superstar (a "Messi-type" talent) can dominate matches; his disproportionate impact can overcome the morale costs of a wide pay gap. Simply, in soccer there appears to be an optimal mid-range of inequality but also a potential benefit to having one extraordinarily paid, game-changing player.

Evidence from the NFL: A similar inverted-U pattern appears in American football. Park (2023) examines twenty years of NFL data and, using system GMM to address reverse causality, finds that team wins increase with salary dispersion up to a Gini coefficient of about 0.55 among active players, after which performance declines. This turning point is useful because NFL rosters are significantly larger than NBA rosters, meaning teams can likely tolerate more pay inequality before team chemistry suffers. The

NBA's smaller 12–15 player rosters and greater reliance on on-court coordination suggest that the optimal level of inequality might occur at a lower Gini value. Park's methodology also highlights methods concern as successful teams might restructure their payrolls in response to performance, causality can run in both directions.

Early NBA Evidence: Empirical findings within the NBA itself have been mixed. Simmons and Berri (2011) distinguish between "explained" salary inequality (pay gaps justified by past performance differences) and "residual" inequality (gaps not justified by performance). They find that only the explained portion of pay disparity correlates positively with team wins. This supports the fairness/cohesion model, as players seem to accept large salary differences when those differences are perceived as merit-based, compared to arbitrary or unjustified disparities may undermine team performance. In another paper, Katayama and Nuch (2011) look at game level NBA data with dynamic panel techniques and find no significant effect of salary dispersion on the probability of winning an individual game. This null result suggests that if pay inequality has an impact, it would likely appear over the long run (affecting season-long efficiency or consistency) rather than in the randomness of a single game.

Contract-Year Performance Patterns: Additional lessons come from studies of player effort incentives. As highlighted above, Stiroh (2007) documents a clear "contract year" effect: players substantially improve their performance in the final year of a contract and often relax after securing a new deal. For team outcomes, this implies that a franchise heavily reliant on players with secure long-term contracts might face an unseen performance drag. Teams might benefit in the short run from underpaid players attempting to get a large contract, but they may also suffer when well-paid players underperform relative to their salaries. This dynamic adds nuance to how to interpret pay inequality, it is not just the distribution at a point in time that matters, but also how contracts and incentives evolve over time.

Summary of Evidence and Hypothesis

Summary of Evidence: Across sports and methods, the relationship between pay inequality and success is not a simple relationship or can be applied the same in every case. However, two patterns emerge consistently. First, a non-linear relationship often fits better than a linear one, as moderate inequality can be beneficial, but too little or too much can be detrimental, highlighting the inverted-U predicted by theory. Second, measurement choices are crucial. How one defines inequality and team performance can change the results. Different studies use different inequality metrics and different performance metrics leads to varied conclusions. These lessons directly inform the design of the empirical work.

Hypotheses: Guided by the theory and prior evidence, the study tests the following key hypotheses:

- **H1 (Tournament Effect):** At low levels of pay dispersion, increasing inequality has a positive effect on team performance. In other words, the linear term on the Gini is expected to be positive when dispersion is modest, reflecting the effort-enhancing impact of tournament-style incentives.

- **H2 (Fairness Effect):** Beyond a certain point, further increases in pay dispersion harm performance. This implies a negative coefficient on the squared Gini term, producing a peak in the performance–inequality curve (i.e. an inverted-U relationship). Past that peak, the fairness/cohesion costs dominate the incentive benefits.

- **H3 (Resource Drain Effect):** Teams that devote a larger share of their payroll to inactive or non-performing players will underperform relative to others with the same active-roster inequality. In practice, for a given Active Gini level, higher shares of inactive salary types are expected to correlate with worse performance, since it indicates less money available to reward and field contributing talent. Injury payments are also a key aspect to control for, due to their random risk which impacts active contracts player performance. This hypothesis reflects the idea that money locked in unproductive contracts or sidelined players undermines team performance regardless of the internal pay gap among active players.

Innovation

This study advances existing literature in several important ways. First, by focusing on cash-based Gini coefficients calculated only on active-roster salaries, it isolates the true pay-dispersion incentives on court rather than conflating them with unproductive obligations. Second, it introduces a composite performance metric that combines scaled VORP with adjusted net rating, offering a more nuanced measure of team efficiency than simple win percentage. Third, the specification explicitly controls for inactive salary shares and injury-related payroll, two factors that prior work often overlooks but that can significantly distort the incentive effects of pay inequality. Finally, to address endogeneity concerns, the analysis employs an instrumental variables approach using lagged general manager turnover and exogenous shifts in luxury tax rules, along with tests for nonlinear tournament and cohesion effects. These methodological refinements, which include more precise inequality measures, a richer performance index, comprehensive controls, and a clear identification strategy, allow the study to deliver insights into how pay structure affects NBA team performance.

Methodology

Sampling frame

This study assembled a balanced panel of 30 NBA franchises from 2017–18 through 2023–24. The 2016–17 season appears only to generate one-year lags and is excluded from estimation. Limiting the window to the post-2017 CBA era avoids structural breaks in cap and luxury-tax rules. The final sample contains 210 team-season observations (30 × 7).

Data collection and integration

All raw files are merged on a team-season key created in R; final panel data appears in the NBA_processed Excel workbook under combined_ts. All empirical analysis was conducted using Stata. The study's econometric techniques included OLS regressions, fixed-effects models, two-stage least squares (instrumental variables), interaction effect models, and an ordered probit for playoff outcomes. These were implemented to ensure robust results and to test various dimensions of the hypothesis.

Table 1

Category	Variables	Source	Integration notes
Payroll	Cash salary, contract type	Spotrac	Salaries prorated for mid-season trades; contracts flagged as active, retained, dead-cap or cap-hold
Performance	Adjusted Net Rating, player VORP	Basketball-Reference	VORP adjusted for mid-season trades; Net Rating pace- and opponent-adjusted
Cap environment	Salary-cap ceiling (ln_CapMax_USD), MinJump_Pct	RealGM CBA tracker	Lagged by one season in all regressions. MinJump_pct captures how much room teams have to raise minimum salaries.
Franchise wealth	Forbes valuation (Inflation Adj to 2023 USD)	Forbes	Logged to reduce skew; lagged one season to avoid simultaneity valuation based on current performance
Management history	GM turnover dummy	RealGM	Equals 1 if a new GM is hired between July 1 t and June 30 t+1

Table 2

Name	Construction	Expected sign
Composite Score *(dependent variable)*	Normalise Adjusted Net Rating and team-summed VORP to 0–1, and multiply	+
Active Gini	Gini (ineq::Gini) of cash shares for *active* player contracts	+
Overall Gini	Gini on all contract types	+
ln(Total Payroll)	Natural log of prior-season cash payroll	+
Pct Inactive	Inactive salary ÷ total payroll	+
Injury Cash Share	Injury cash ÷ total payroll	+
Luxury Tax	Dummy = 1 if tax payer	0, 1
ln(Franchise Valuation)	Log of prior-season Forbes value	+

Table 3: Descriptive Statistics

	Obs	Mean	Std. Dev.	Min	Max
Composite Score	210	0.273	0.191	0.000	0.986
Win–Loss %	210	0.499	0.144	0.171	0.793
Active Gini	210	0.546	0.074	0.304	0.744
Overall Gini	210	0.610	0.078	0.304	0.777
ln(Total Payroll)	210	18.690	0.177	18.189	19.160
Luxury Tax Rate	210	0.210	0.408	0.000	1.000
% Active Salary	210	0.849	0.138	0.348	1.000
% Inactive Salary	210	0.151	0.138	0.000	0.652
Injury Cash Share	210	0.195	0.095	0.042	0.524
GM Turnover	210	0.162	0.369	0.000	1.000
ln(Cap Max USD)	210	18.538	0.102	18.412	18.728
Min Jump %	210	0.119	0.161	0.000	0.501

Why Cash Matters

Cap-hit accounting can be manipulated through exceptions, cap holds and deferred guarantees that hide the true cost of talent under the salary cap. Comparatively, cash compensation records the exact dollars each franchise pays players every season, making it a transparent and manipulation-resistant measure of team investment. Cash salaries also reflect owner and front-office choices about personnel outlays rather than league revenue formulas or collective-bargaining provisions. From a player's perspective, real take-home pay drives motivation, contract-year effort and locker-room comparisons. Previous papers Lazear (2000) show that visible compensation is the primary driver of effort, so cash-based payroll shares offer a straightforward, comparable metric for linking team resources to player incentives and on-court performance.

Inequality and Performance Measures

The main independent variable is the Active Gini coefficient, calculated with R's ineq package on each player's share of team cash payroll. For robustness, Overall Gini was also computed, which includes all types of contracts, not just players on active roster. Active Gini focuses to isolate disparities among contributors on the active roster. To allow for a non-linear effect, both the Gini coefficient and its square enter the regression specifications.

The dependent variable is a Composite Score that blends team efficiency and roster talent on a 0–1 scale. Efficiency comes from Adjusted Net Rating, which measures point margin per 100 possessions after adjusting for pace and opponent strength. This study measures talent using team-summed Value Over Replacement Player (VORP), which reflects how much value each player adds above a replacement-level player. Although VORP is often interpreted as converting to approximately 2.7 team wins per point over a full season, this conversion was not used for analysis. Instead, VORP is combined with Adjusted Net Rating to create a Composite Score that captures both total player value and team efficiency. Each component is rescaled to the [0, 1] interval relative to the sample's worst and best team seasons, then the two normalized values are multiplied resulting in the composite score. Higher scores reflect teams that most effectively convert talent into performance. This metric overcomes the shortcomings of win percentage by filtering out randomness and schedule imbalances and by rewarding true on-court execution. In practical terms it answers the general manager's question: given our roster's talent, how well are we turning it into winning basketball?

Table 4 highlights the five best and five worst team seasons in the sample to help interpret the range of values for VORP, Net Rating, and Composite Score in context.

Table 4:

Dependent Variable Justification

Top and Bottom 5 Team-Seasons by Composite Score (Illustrative Examples)

Team	Season	Total Vorp	Adj Net Rtg	Win%	Norm Vorp	Norm Net Rtg	Composite Score
BOS	2023	22.200	11.110	0.780	1.000	0.986	0.986
HOU	2017	19.100	8.370	0.793	0.871	0.861	0.750
UTA	2020	17.700	9.200	0.722	0.813	0.899	0.731
MIL	2019	17.800	8.960	0.767	0.817	0.888	0.726
MIL	2018	18.300	7.660	0.732	0.838	0.829	0.695
ORL	2020	-0.700	-9.200	0.292	0.050	0.058	0.003
CLE	2018	-1.100	-9.820	0.232	0.033	0.030	0.001
SAS	2022	-1.300	-9.650	0.268	0.025	0.038	0.001
OKC	2020	-1.300	-9.960	0.306	0.025	0.024	0.001
CHA	2023	-1.900	-10.480	0.256	0.000	0.000	0.000

Table 5: DV Justification

	Lagged Win–Loss %	Lagged Composite Score
Lagged Win–Loss %	0.558***	
	(8.72)	
Lagged Composite Score		0.413***
		(8.26)
Intercept	0.221***	0.388***
	(6.45)	(21.15)
R-squared	0.300	0.281
RMSE	0.120	0.122

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

To demonstrate that the Composite Score is at least as predictive of future success as traditional wins, two lagged-performance models are compared. First, regressing next season's win percentage on its own lag has a coefficient of 0.558 ($t = 8.72$, $R^2 = 0.300$, RMSE = 0.120). Second, using lagged composite score instead produces a coefficient of 0.413 ($t = 8.26$, $R^2 = 0.281$, RMSE = 0.122). The nearly identical R^2 in both models show that the composite score predicts future performance almost as well as raw percentage, yet it allows depth in interpretation by capturing efficiency and individual contribution. For these reasons, Composite Score is used as the primary dependent variable.

Controls and Clustering

To isolate the effect of pay dispersion on performance, each model includes the following control variables:

- **Pct Inactive:** Share of payroll tied up in non-playing contracts (dead cap, retained salary, cap holds).
- **Injury Cash Share:** Share of payroll paid to players who missed games due to injury.
- **Luxury Tax:** Indicator equal to 1 if the team exceeded the luxury-tax threshold that season.
- **ln(Franchise Valuation):** Natural log of Forbes' franchise valuation, lagged one season.
- **GM Turnover:** Indicator equal to 1 if a new general manager was appointed between July 1 and June 30 around the season.

All standard errors are heteroskedasticity-robust and clustered by team_id to account for within-team correlation over time.

Results

OLS Regressions- Gini

Table 6: OLS Gini Regressions

	(1) Composite _Score	(2) Composite _Score	(3) Composite _Score	(4) Composite _Score	(5) Composite _Score	(6) Composite _Score
Gini	0.299*	0.174	0.0376	0.394***	0.345**	0.339**
	(0.165)	(0.161)	(0.146)	(0.133)	(0.139)	(0.145)
ln_Team_Total		0.329***	0.219***	0.239***	0.175***	0.121*
		(0.0644)	(0.0616)	(0.0569)	(0.0652)	(0.0730)
Pct_Inactive			-0.635***	-0.570***	-0.559***	-0.528***
			(0.0687)	(0.0629)	(0.0614)	(0.0633)
Injury_Cash_Share				-0.838***	-0.810***	-0.832***
				(0.101)	(0.102)	(0.106)
Pays_LuxTax					0.0546*	0.0750**
					(0.0283)	(0.0295)
L.ln_Team_Val						-0.00199
						(0.0272)
Constant	0.0904	-5.987***	-3.752***	-4.181***	-2.969**	-1.972
	(0.0993)	(1.189)	(1.143)	(1.059)	(1.218)	(1.355)
r2_a	0.0103	0.0974	0.292	0.443	0.450	0.455
aic	-100.00	-118.3	-168.3	-217.8	-219.3	-187.9

Standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

The six OLS models below examine how payroll inequality, measured by the Gini coefficient of all contract types, relates to team performance. It begins with a simple regression of Composite Score on Gini and then add controls in sequence: total payroll, inactive contract share, injury cash share, luxury tax status, and last season's team valuation to isolate the independent effect of pay dispersion.

Model 1. In this baseline specification, Composite Score (ranging from 0 [worst team] to 1 [best team during period]) is regressed on the Gini coefficient, which spans 0 (perfectly equal pay) to 1 (perfectly unequal pay). The estimated coefficient of 0.299 ($p < 0.10$) means that shifting from perfectly equal salaries to perfectly unequal salaries is associated with a 0.299-point rise in Composite Score, equivalent to a 29.9 percent improvement in overall team performance. This simplest model explains only 1.5 percent of the variation ($R^2 = 0.015$).

Model 2. Adding ln(total payroll) to capture scale effects, finds that a 1 percent increase in total payroll corresponds to a 0.00329-point gain in Composite Score ($p < 0.01$), or about a 0.329 percentage-point improvement for a full 100 percent spending increase. Once budget size is held constant, the Gini coefficient falls to 0.174 ($p > 0.10$), indicating that part of Model 1's apparent inequality effect reflects overall spending differences. Model fit rises to $R^2 = 0.120$.

Model 3. Adding the share of payroll tied to inactive contracts (Pct_Inactive). A one-unit increase in inactive share (from 0 percent to 100 percent) reduces Composite Score by 0.635 points ($p < 0.01$), or a 63.5 percentage-point drop. Controlling for both payroll size and inactive share, ln(total payroll) still adds 0.00219 points per 1 percent spending increase ($p < 0.01$), while Gini contributes only 0.038 points ($p > 0.10$). Model fit rises to $R^2 = 0.302$.

Model 4. Adding injury-cash share alongside inactive share, each 1 percent increase in injury-cash share reduces Composite Score by 0.838 points ($p < 0.01$), and inactive share still subtracts 0.570 points ($p < 0.01$). After accounting for these non-productive payroll components, ln(total payroll) adds 0.00239 points per 1 percent spending increase ($p < 0.01$), and Gini rebounds to a 0.394-point gain ($p < 0.01$), or 39.4 percentage points. Model fit rises to $R^2 = 0.454$.

Model 5. Introducing a luxury-tax indicator, tax-paying teams score 0.055 points higher on average ($p < 0.10$), equal to a 5.5 percentage-point advantage. In this full specification, ln(total payroll) adds 0.00175 points per 1 percent spending increase ($p < 0.01$), injury-cash share subtracts 0.810 points ($p < 0.01$), inactive share subtracts 0.559 points ($p < 0.01$), and Gini contributes a 0.345-point boost ($p < 0.05$), or 34.5 percentage points. This model explains 47.8 percent of the variation ($R^2 = 0.478$).

Model 6. Adding lagged ln(team valuation) yields an insignificant coefficient (–0.002, $p > 0.10$), showing no detectable valuation effect. Holding valuation constant, a 1 percent payroll increase adds 0.00121 points ($p < 0.10$), injury-cash share subtracts 0.832 points ($p < 0.01$), inactive share subtracts 0.528 points ($p < 0.01$), paying the luxury tax predicts a 0.075-point gain ($p < 0.05$), and Gini still adds 0.339 points ($p < 0.05$). This fullest model explains 49.2 percent of the variation ($R^2 = 0.492$).

Diagnostics. Model 5 is the preferred specification based on its lowest AIC = –219.3 vs. –187.9 for Model 6), reflecting the best balance of fit and simplicity. In Model 5, the joint null that all coefficients equal zero is rejected ($F(6, 173) = 36.86$, $p < 0.001$), confirming overall explanatory power. Variance-inflation factors for this model range from 1.13 to 1.37 (mean VIF = 1.37), all well below the cutoff of VIF=10 for any variable, indicating multicollinearity is not a concern. All standard errors are heteroskedasticity-robust and clustered by team_id.

OLS Regressions- Active Gini

Table 7: OLS Active Gini Regressions

	(1) Composite _Score	(2) Composite _Score	(3) Composite _Score	(4) Composite _Score	(5) Composite _Score	(6) Composite _Score
Active_Gini	0.547***	0.340**	0.0332	0.259*	0.181	0.149
	(0.176)	(0.172)	(0.149)	(0.133)	(0.142)	(0.149)
ln_Team_Total		0.302***	0.218***	0.235***	0.169***	0.122
		(0.0672)	(0.0626)	(0.0578)	(0.0649)	(0.0742)
Pct_Inactive			-0.633***	-0.566***	-0.561***	-0.532***
			(0.0718)	(0.0632)	(0.0628)	(0.0647)
Injury_Cash_Share				-0.768***	-0.741***	-0.756***
				(0.0961)	(0.0976)	(0.103)
Pays_LuxTax					0.0593**	0.0805***
					(0.0294)	(0.0308)
L.ln_Team_Val						0.000307
						(0.0286)
Constant	-0.0261	-5.549***	-3.732***	-4.024***	-2.775**	-1.876
	(0.0950)	(1.227)	(1.155)	(1.070)	(1.212)	(1.378)
r2_a	0.0403	0.108	0.292	0.429	0.437	0.441
aic	-106.5	-120.9	-168.2	-212.5	-214.4	-183.4

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

The six OLS models below examine how inequality among active contract types alone, measured by the Active Gini coefficient, relates to team performance. Starting with a simple regression of Composite Score on Active Gini and then add controls in sequence: total payroll, inactive contract share, injury cash share, luxury tax status, and last season's team valuation to isolate the independent effect of pay dispersion.

Model 1. In this baseline, Composite Score (0 worst team to 1 best during period) is regressed on Active Gini, which runs from 0 (equal active pay) to 1 (one active player receives all cash). The coefficient of 0.547 ($p < 0.01$) means shifting from perfectly equal active salaries to perfectly unequal active salaries is associated with a 0.547-point rise in Composite Score, or a 54.7 percentage-point improvement in overall performance. This simple model explains 4.5 percent of the variation ($R^2 = 0.0449$).

Model 2. Adding ln(total payroll) to capture scale effects shows that a 1 percent increase in payroll is associated with a 0.00302-point gain in Composite Score ($p < 0.01$). Holding spending constant, Active

Gini's effect falls to 0.340 ($p < 0.05$), indicating part of the raw pay-dispersion link simply reflected budget size. Model fit increases to $R^2 = 0.1170$.

Model 3. Introducing the share of payroll tied to inactive contracts (Pct_Inactive) reveals that a one-unit increase, from 0% to 100% inactive spend, reduces Composite Score by 0.633 points ($p < 0.01$), or a 63.3 percentage-point drop. Controlling for both spending and inactive share, ln(total payroll) still adds 0.00218 points per 1 percent spending increase ($p < 0.01$), while Active Gini's coefficient becomes a non-significant 0.033. Model fit rises to $R^2 = 0.3018$.

Model 4. Adding injury cash share alongside inactive share, each additional unit of injury cash reduces Composite Score by 0.768 points ($p < 0.01$), and inactive share still subtracts 0.566 points ($p < 0.01$). After netting out these non-productive payroll components, ln(total payroll) contributes 0.00235 points per 1 percent spend ($p < 0.01$), and Active Gini rebounds to a 0.259-point gain ($p < 0.10$), or 25.9 percentage points. Model fit rises to $R^2 = 0.4399$.

Model 5. Introducing a luxury-tax indicator shows that tax-paying teams score 0.059 points higher on average ($p < 0.05$), a 5.9 percentage-point advantage. In this specification, ln(total payroll) adds 0.00169 points per 1 percent increase ($p < 0.01$), injury cash share subtracts 0.741 points ($p < 0.01$), inactive share subtracts 0.561 points ($p < 0.01$), and Active Gini's effect is 0.181 ($p > 0.10$). This model explains $R^2 = 0.4502$ of the variation.

Model 6. Adding last season's ln(team valuation) yields an insignificant coefficient of 0.00031 ($p > 0.10$), indicating no detectable valuation effect. Holding valuation constant, ln(total payroll) adds 0.00122 points per 1 percent spend ($p < 0.10$), injury cash share subtracts 0.756 points ($p < 0.01$), inactive share subtracts 0.532 points ($p < 0.01$), and paying the luxury tax predicts a 0.080-point gain ($p < 0.01$), while Active Gini remains at 0.149 ($p > 0.10$). This fullest model explains $R^2 = 0.4598$.

Diagnostics. Model 5 is selected as the preferred specification based on its lowest AIC (–214.4 vs. –212.5 for Model 4 and –183.4 for Model 6), reflecting the optimal trade-off between fit and simplicity. In Model 5, the joint null that all coefficients equal zero is rejected ($F(5, 204) = 47.67$, $p < 0.001$), confirming collective explanatory power. Variance-inflation factors range from 1.08 to 1.56 (mean = 1.32), all well below the threshold of 10, indicating multicollinearity is not a concern. Standard errors are robust to heteroskedasticity and clustered at the team level (team_id).

Instrumental Variable Regressions

Table 8: First-Stage Regressions for IV Models

	(1) IV1	(2) IV2	(3) IV3	(4) IV4
Lagged Cap	-0.392***	-0.422***	-0.422***	-0.422***
	(0.0818)	(0.0806)	(0.0806)	(0.0806)
Lagged Payroll	0.279***	0.271***	0.271***	0.271***
	(0.0392)	(0.0383)	(0.0383)	(0.0383)
Min Salary Jump %	-0.144			
	(0.124)			
_cons	2.611**	3.313***	3.313***	2.768**
	(1.276)	(1.194)	(1.194)	(1.194)
R-squared	0.225	0.221	0.221	0.221
Adj. R-squared	0.212	0.212	0.212	0.212
Observations	180	180	180	180

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Second-Stage Regressions for IV Models- Composite Score

	(1) Composite_Score	(2) Composite_Score	(3) Composite_Score	(4) Composite_Score
cActive_Gini	0.848*	0.902**	0.171	0.611
	(0.441)	(0.442)	(0.455)	(0.496)
ln_Team_Total	0.153	0.147	0.126	0.0927
	(0.0952)	(0.0941)	(0.0853)	(0.139)
Pct_Inactive	-0.458***	-0.451***	-0.403***	-0.445***
	(0.0624)	(0.0643)	(0.0494)	(0.0809)
Injury_Cash_Share	-0.892***	-0.901***	-0.776***	-0.755***
	(0.120)	(0.119)	(0.0926)	(0.190)
L.Composite_Score			0.385***	
			(0.0772)	
cActive_Gini2				-6.617
				(6.922)
_cons	-2.342	-2.228	-1.982	-1.205
	(1.791)	(1.770)	(1.615)	(2.613)
R-squared	0.395	0.387	0.551	0.285
Adj. R-squared	0.381	0.373	0.538	0.264
AIC	-167.1	-164.5	-218.8	-134.8
Observations	180	180	180	180

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Second-Stage Regressions for IV Models- Win-Loss Percentage Robustness Check

	(1) Win_Loss_Pct	(2) Win_Loss_Pct	(3) Win_Loss_Pct	(4) Win_Loss_Pct
cActive_Gini	0.821**	0.841**	0.390	0.694*
	(0.358)	(0.361)	(0.396)	(0.359)
ln_Team_Total	0.0514	0.0493	0.0332	0.0221
	(0.0581)	(0.0574)	(0.0538)	(0.0782)
Pct_Inactive	-0.404***	-0.402***	-0.358***	-0.399***
	(0.0682)	(0.0689)	(0.0512)	(0.0736)
Injury_Cash_Share	-0.663***	-0.667***	-0.608***	-0.593***
	(0.0838)	(0.0835)	(0.0647)	(0.131)
L.Win_Loss_Pct			0.325***	
			(0.0883)	
cActive_Gini2				-3.317
				(4.571)
_cons	-0.269	-0.228	-0.107	0.285
	(1.096)	(1.082)	(1.030)	(1.471)
R-squared	0.416	0.411	0.565	0.353
Adj. R-squared	0.403	0.398	0.552	0.334
AIC	-277.2	-275.6	-328.0	-256.6
Observations	180	180	180	180

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Instrumental Variable Regressions

A central concern with the OLS results is the risk of reverse causality. Teams that perform well may be more likely to adopt unequal salary structures, which could bias the estimated effect of Active Gini. To address this, a two-stage least squares (2SLS) regression is implemented with robust standard errors clustered at the team level. The endogenous regressor, Active Gini, captures the degree of payroll inequality among active players and ranges from 0, indicating perfect equality, to 1, indicating maximum inequality. It is instrumented using three predetermined or lagged financial variables: the prior season's salary cap (ln_CapMax_USD), lagged total payroll (ln_Team_Total), and the minimum salary jump percentage (MinJump_Pct) determined by league policy. These instruments are selected based on both theoretical relevance and time based exogeneity. Salary cap and payroll figures are set before the season begins, and the salary jump percentage reflects collective bargaining agreements that apply uniformly across teams.

While the luxury tax indicator was included as a control in OLS Model 5, which was selected as the preferred specification based on the lowest AIC value (–214.4), it is not included it as a control in the IV regression. The difference in AIC between Model 5 and the next-best model was small, so leaving out the luxury tax in the IV model does not sacrifice much in terms of fit. More importantly, including it could introduce bias. The luxury tax is not always determined before the season starts. Teams can cross the tax threshold during the season depending on how their performance unfolds or if they make trades. Because of this, it may partly reflect a team's success instead of helping to predict it. Since the luxury tax can be affected by team performance, it is excluded from the IV model to avoid controlling for something that might be a result of performance rather than a cause.

Other control variables are retained because they are less likely to violate this condition. Total payroll (ln_Team_Total) is measured for the current season, but most NBA salary commitments are made during the offseason through guaranteed contracts. While minor adjustments can occur in-season, the majority of payroll reflects pre-season financial planning rather than reactions to team success. Keeping this variable helps control for the overall level of investment and allows the model to focus on how that money is distributed. The percentage of inactive salary and injury-related pay are also included because they capture nonperformance related constraints on team resources. Inactive salary typically results from earlier contract decisions or roster management rules, and injury costs reflect random shocks outside of a team's control. These controls help isolate the impact of pay inequality among active players by accounting for the resources that are unavailable for on-court performance.

Model IV1: The first-stage regressions show that two of the three instruments are strong predictors of Active Gini. The log of the NBA salary cap (ln_CapMax_USD) and the log of total team payroll (ln_Team_Total) which are close to or above the cutoff of 10 for instrument strength, with F-statistics of 9.4 and 14.7. However, the third instrument, MinJump_Pct, is weak with an F-statistic of 1.1. Since this model is overidentified, Hansen's J is used to assess whether the instruments are valid. The J test checks whether the extra instruments are correlated with the error term in the second stage. A high p-value means it fails to reject the null hypothesis of instrument validity. In this model, the Hansen J p-value is 0.27, supporting the claim that the instruments are appropriate. In the second stage, Active Gini has a positive and marginally significant effect on team performance (coefficient = 0.848, $p < 0.10$). This suggests that if a team shifted from perfect pay equality to maximum inequality among active players, its Composite Score would be expected to rise by about 0.85 points. The control variables behave similarly to those in the OLS models: inactive salary and injury-related pay are both negatively and significantly associated with performance, while payroll has a positive but insignificant effect. This model explains about 40 percent of the variation in Composite Score.

Model IV2: To improve instrument strength, the weak instrument MinJump_Pct is removed and only ln_CapMax_USD and ln_Team_Total is kept. These two instruments show a strong first-stage F-statistic of 19.08, suggesting they are effective predictors of Active Gini. Because this model is just identified, meaning the number of instruments equals the number of endogenous variables, Hansen's J test cannot be used to test instrument validity. The Hansen J test requires an overidentified model, where there are more instruments than endogenous variables, allowing one to check whether the extra instruments are valid. In this case, the instruments are just able to estimate the causal effect, but there is no way to test their validity statistically. Instead, their validity must be supported by economic theory. The variable ln_CapMax_USD reflects the league's salary cap, which is determined before the season and applies equally to all teams. This makes it clearly exogenous. Although ln_Team_Total captures current-season spending and could theoretically be influenced by midseason trades, most of a team's payroll is determined before the season through guaranteed contracts. As a result, total spending primarily reflects planned financial decisions rather than responses to team performance. In the second stage, the estimated effect of Active Gini increases to 0.902 and is statistically significant at the 5 percent level. Control variables remain consistent in both direction and significance. This model explains roughly 39 percent of the variation in performance and is selected as the preferred specification because of its stronger instruments and more precise beta coefficients.

Model IV3: To account for performance momentum, lagged Composite Score is added as a control. Instrument strength remains strong, with a first-stage F-statistic of 14.17, and Hansen's J p-value of 0.20 again supports instrument validity. The coefficient on Active Gini drops to 0.171 and becomes statistically insignificant. At the same time, the lagged outcome strongly predicts current performance (coefficient = 0.385, $p < 0.01$), suggesting that past results may explain much of the relationship seen in the other models. Other control variables remain stable, and the model explains a more of the variation in performance ($R^2 = 0.551$).

Model IV4: Finally, whether the relationship between pay inequality and team performance is nonlinear is tested by instrumenting both Active Gini and its squared term. To reduce multicollinearity between the two, Active Gini is centered before squaring it, since the original small values caused inflated VIF. In the first stage, the instruments are not strong enough to predict the squared term reliably. In the second stage, neither Active Gini nor its squared term is statistically significant. The signs of the beta coefficients potentially suggest inverted-U relationship, where moderate inequality might be more effective than very low or very high levels. However, due to weak instruments and statistically insignificant results, a clear conclusion can't be formed. This model explains a smaller share of the variation in team performance ($R^2 = 0.285$).

Summary: The IV results continue to support the OLS finding that greater pay dispersion among active players can boost team outcomes, but they also reveal how much of that boost reflects carryover from the prior season rather than a pure one-year incentive shock.

Composite Score (2nd-stage): In the preferred IV 2, Active Gini is positive and significant (coefficient = 0.902, $p < 0.05$), closely matching the OLS pattern. Once lagged Composite Score is added in Model 3, the Gini effect falls to 0.171 (not significant) while the lag term itself is highly significant (coefficient = 0.385, $p < 0.01$), indicating that past efficiency and VORP largely drive current performance.

Win-Loss Percentage (2nd-stage robustness): Replacing the dependent variable with win percentage shows a similarly strong effect in IV 2 (coefficient = 0.841, $p < 0.05$). In Model 3, the Gini coefficient again drops and loses significance (coefficient = 0.390, not significant) as the lagged win percent (coefficient = 0.325, $p < 0.01$) captures most of the variation.

In every specification Active Gini remains positive, but Model 3's results reflect that performance persistence explains a substantial share of the observed inequality effect. Model 4's weak instruments limit the ability to draw conclusions about a potential nonlinear relationship. Overall, unequal pay among active players appears to enhance team success, partly through momentum from one season into the next.

Ordered Probit Playoff

Table 11: Order Probit Playoff

	(1)
	round_ord
round_ord	
Injury_Cash_Share	-3.849***
	(1.027)
Pct_Inactive	-3.515***
	(0.664)
ln_Team_Total	3.665***
	(0.617)
Season=2017	0
	(.)
Season=2018	-0.0858
	(0.252)
Season=2019	-0.110
	(0.309)
Season=2020	-0.297
	(0.362)
Season=2021	-0.299
	(0.334)
Season=2022	-0.939**
	(0.384)
Season=2023	-1.324***
	(0.439)
cut1	66.74***
	(11.49)
cut2	67.64***
	(11.47)
cut3	68.20***
	(11.48)
cut4	68.65***
	(11.49)
r2_p	0.141
chi2	113.6
df_m	9

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Probit Regression: Playoff Advancement

To examine how structural team factors influence playoff outcomes, an ordered probit model is used to estimate where the dependent variable (round_ord) captures the furthest playoff round reached by each team in each season. This model is appropriate because the dependent variable is ordered categorical, not continuous, which makes OLS unsuitable. The ordered probit approach estimates the probability that a team falls into each of several ordered playoff categories by modeling a latent index: an unobserved continuous variable that reflects underlying playoff performance.

This latent playoff index can be thought of as a hidden strength score, combining the effects of payroll, injuries, and roster composition into a single underlying value. The model assumes teams are assigned to a playoff category based on where they fall relative to several estimated cutoff points along this index. For example, teams whose latent playoff index falls below the first cutoff do not qualify for the playoffs, while those whose index exceeds the final threshold advance to subsequent rounds, including the first round, conference semifinals, conference finals, and the NBA Finals, depending on their position relative to the estimated cutoff points. The interpretation of the coefficients are not direct changes in playoff probabilities. Instead, a positive coefficient indicates that an increase in the corresponding explanatory variable pushes a team higher on the latent playoff index, which increases the probability of reaching more advanced rounds.

I include three primary explanatory variables: Injury Cash Share, Pct Inactive, and ln_Team_Total, the log of total team payroll. These variables reflect how efficiently teams deploy their salary resources. Season fixed effects is included to control for year-specific shocks. Statistical significance is evaluated using robust standard errors clustered by team ID.

The results show that teams allocating a larger share of payroll to injured players tend to perform significantly worse in the postseason. Specifically, a one-percentage-point increase in Injury Cash Share is associated with a 3.85-point reduction in the latent playoff index ($p < 0.01$). Similarly, higher inactive contract shares are detrimental: a one-percentage-point increase in Pct Inactive lowers the index by 3.52 points ($p < 0.01$). These effects are substantial. The estimated cutoff points that separate playoff rounds lie roughly 1 to 1.5 points apart, so even modest increases in injury or inactive spending can shift a team down one or two playoff stages.

Comparatively, team payroll has a strong positive association with playoff success. A 1% increase in ln_Team_Total is linked to a 3.67-point increase in the latent playoff index ($p < 0.01$). Based on the same cutoff spacing, this increase could plausibly move a team up two or more stages in playoff advancement. Taken together, these findings highlight how material investments in active, healthy players can meaningfully improve a team's postseason trajectory.

Among season effects, only 2022 and 2023 display significant deviations from the 2017 reference category. The 2022 dummy is associated with a 0.939-point decrease ($p < 0.05$), while 2023 drops the latent index by 1.324 points ($p < 0.01$). These negative shifts may reflect changes introduced by the new Collective Bargaining Agreement (CBA) that took effect in 2023 (NBA and NBPA, 2023), which implemented stricter luxury tax penalties and altered roster construction incentives. Additionally, the expanded playoff format introduced in prior seasons, such as the introduction of the play-in tournament, may have influenced the distribution of teams across playoff categories, though these structural shifts fall outside the primary scope of this analysis.

Cutoff points (cut1 through cut4) separating playoff stages are all statistically significant and consistent, confirming that the ordered structure is appropriate. The model explains roughly 14.1% of the variation in playoff progression ($R^2 = 0.141$), and the joint chi-squared statistic (113.6) indicates strong overall model significance.

In summary, the ordered probit analysis shows that team performance in the postseason is strongly tied to how efficiently payroll is allocated. Reducing injury-related and inactive spending while boosting active investment meaningfully increases a team's chances of progressing through the playoffs.

Interaction Term

Table 12: Interaction Terms

	(1) Composite_Score	(2) Composite_Score	(3) Win_Loss_Pct	(4) Composite_Score
ln_Team_Total	0.394*** (0.0698)	0.299*** (0.0973)	0.281*** (0.0516)	0.267*** (0.0897)
Pct_Inactive	-0.547*** (0.0710)	-0.658*** (0.112)	-0.466*** (0.0590)	-0.524*** (0.0740)
c_top3	0.118 (0.108)	0.0984 (0.187)	0.140 (0.0948)	-0.0930 (0.130)
c_inj	-0.734*** (0.106)	-0.755*** (0.174)	-0.522*** (0.0734)	-0.795*** (0.117)
c_top3_inj	0.154 (0.808)	0.0256 (1.241)	0.0411 (0.850)	0.453 (1.194)
year_trend	-0.0179** (0.00852)	-0.00913 (0.0117)	-0.0145** (0.00635)	
Season=2017				0 (.)
Season=2018				0.0109 (0.0274)
Season=2019				-0.0238 (0.0375)
Season=2020				-0.0122 (0.0396)
Season=2021				0.0407 (0.0392)
Season=2022				-0.0596 (0.0460)
Season=2023				-0.0648 (0.0551)
Constant	-6.943*** (1.281)	-5.153*** (1.790)	-4.625*** (0.947)	-4.632*** (1.658)

r2_a	0.439	0.370	0.482	0.422
aic	-214.3	-115.1	-350.5	-293.0

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Interaction Model: Top-Heavy Spending and Injury Risk

To test whether top-heavy salary distributions are more harmful when teams experience injuries, four interaction models are used that include both the centered share of payroll paid to the top three players (c_top3) and its interaction with injury share (c_top3_inj). All models control for Pct Inactive, ln_Team_Total, and Injury Cash Share. Models (1), (2), and (4) use Composite Score as the dependent variable, while Model (3) uses Win-Loss Percentage. Model (2) introduces a year trend, and Model (4) includes full season fixed effects.

Model (1) serves as the baseline interaction model. It finds that while Pct Inactive (−0.547, $p < 0.01$), ln_Team_Total (0.394, $p < 0.01$), and Injury Cash Share (−0.734, $p < 0.01$) all have strong effects, neither the top three salary share (c_top3) or its interaction with injuries (c_top3_inj) is significant. The interaction term's coefficient is small (0.154) and imprecise, providing no evidence of a multiplicative relationship between top heavy rosters and injury burden. The adjusted R^2 is 0.439, and AIC = −214.3.

Model (2) adds a linear year trend and highlights similar conclusions. While the year coefficient itself is significant (−0.0179, $p < 0.05$), all main and interaction effects maintain similar size and significance. The interaction coefficient shrinks to 0.0256 and remains non-significant. This reinforces that no year trends do not alter the core findings. The adjusted R^2 falls to 0.370, indicating slightly worse fit relative to Model (1).

Model (3) tests the relationship using Win-Loss Percentage instead of Composite Score. Results are highly consistent: ln_Team_Total (0.281), Pct Inactive (−0.466), and Injury Cash Share (−0.522) are all significant at the 1% level. Again, neither c_top3 (0.140) or the interaction term (0.0411) is statistically significant. Despite the different outcome variable, the key takeaway is consistent, as injuries and top-heavy rosters do not appear to compound. This model achieves the highest adjusted R^2 of 0.482, further validating its fit.

Model (4) includes season fixed effects, replacing the year trend. Control variables stay significant and directionally stable. ln_Team_Total remains strong (0.267, $p < 0.01$), while Pct Inactive (−0.524) and Injury Cash Share (−0.795) continue to weaken performance. The interaction term is slightly larger (0.453) but still very imprecise, with a standard error of 1.194, leaving it statistically irrelevant. Adjusted R^2 = 0.422.

Discussion

This study offers new insights into the economic consequences of NBA roster construction by empirically testing how salary inequality shapes team performance, with a particular focus on active player compensation. Through a sequence of OLS, instrumental variable, interaction, and ordered probit models, the results point toward a clear message: when pay inequality is concentrated among active contributors, team performance improves. These findings broadly support tournament theory's central prediction: pay gaps can incentivize greater effort and performance. At the same time, they show that not all inequality is created equal.

The OLS models reveal that Active Gini, the measure of inequality across active roster contracts, has a positive and often significant association with team performance. The effect is most visible when vital controls are included, particularly the controls of injury-related salary and inactive player payroll. In models without them, Gini and Active Gini appear stronger than they really are, likely because deadweight salary (like injured or waived players) biases performance downward due to no production, making inequality look falsely beneficial. Once these non-contributing salaries are netted out, the positive effect of pay dispersion among active players remains, though somewhat reduced in size. From a labor economics standpoint, this is consistent with a tournament system: teams perform better when there are meaningful salary stakes among players who are actually producing.

The instrumental variables models take this one step further. By using lagged cap size and prior payroll as instruments for Active Gini, concerns about reverse causality are addressed: better teams might be able to justify inequality, rather than the other way around. In the preferred IV specification (Model IV2), the effect of Active Gini on Composite Score rises to 0.902 and is statistically significant ($p < 0.05$). This suggests a causal interpretation: controlling for roster size, valuation, and structural inefficiencies, greater active pay inequality leads to better team outcomes. Part of this may reflect not just incentives, but also the premium that teams must pay for exceptional talent. In the NBA, game-changing players can be so impactful that their contracts alone drive much of the team's output. However, when lagged performance is added (Model IV3), the Gini effect disappears. This signals that some of the inequality-performance link may be driven by momentum, not structure alone, a subtle but important point in identifying when and why inequality works.

I also explore whether the inequality-performance relationship is nonlinear by testing a squared Gini term in IV4. Theory might suggest an inverted-U shape, where too little or too much inequality becomes problematic, but our instruments lack the strength to say anything definitive. The squared Gini term is negative but insignificant. In this case, future research may need policy shocks or natural experiments to more confidently test for nonlinear effects.

The interaction term analysis challenges a popular but untested assumption in basketball discussion: that injuries to high-paid players are uniquely damaging because of how much cap space they consume. While injuries and top-heavy payrolls each reduce team performance when evaluated separately, there is no statistically significant interaction effect found. This means that while both injury and inefficient salary allocation are harmful, they do not appear to compound. Whether a team's injuries come from a role player or a star, the damage appears consistent in magnitude. From a managerial perspective, this shifts the conversation from avoiding top-heaviness to simply minimizing injuries altogether, regardless of contract size. It also reinforces that injury is a mostly random risk, and its occurrence, regardless of who is affected, can meaningfully reduce team output and increase strain on remaining players. This highlights the importance of proactive injury prevention and load management.

Perhaps most impactful is the ordered probit model. Here, performance metrics are not just looked at but actual playoff progression. The latent playoff index underlying this model captures the hidden strength of a team, the payoff to resource efficiency, health, and strategy. Findings show that injury cash share and inactive salary sharply lower a team's latent playoff score. Even modest increases in either can cause a team to drop an entire playoff tier (for example, from conference semifinals to a first-round exit). Conversely, payroll size positively and significantly improves the likelihood of advancing. This finding brings to life the idea that money, when spent well, pays off in playoff results, not just advanced metrics. However, one must also recognize a potential complication: some teams knowingly take on bloated or inactive contracts as part of rebuilding process. In these situations, teams may temporarily depress their performance index in exchange for future assets, such as draft picks or cap flexibility. This introduces a form of reverse causality, where poor performance reflects intentional restructuring rather than mismanagement or inefficiency. Recognizing this, the latent playoff index needs to be interpreted in the context of team strategy and timing. For rebuilding teams, poor playoff outcomes may be a rational choice, not a failure. This nuance adds complexity to evaluating how efficient or inefficient a roster truly is during cyclical changes.

So, what do these results mean for different stakeholders in the league?

General Managers and Front Offices: The data offers clear evidence that concentrating payroll among active players while carefully managing injury exposure is a formula for success. Roster building strategies that avoid deadweight contracts and preserve cap flexibility for healthy contributors yield the highest returns. GMs should invest in not just top talent but the training, recovery, and analytics infrastructure to keep those players on the floor. Salary inequality, when aligned with availability and effort, is a competitive asset, not a liability. That said, inequality is not inherently good or bad, it depends on how it is managed internally. Organizational culture, perceived fairness, and clarity of roles play a large role in whether inequality motivates or demoralizes. Formal strategies, like contract structures and usage decisions, and informal ones, like communication and respect, determine how salary gaps are perceived by the locker room. Additionally, taking care of players through injury management and minimizing inactive turnover signals a coherent mission and builds trust. The perception of management's decisions, how they allocate resources, retain contributors, and invest in health, can either unify or divide a roster.

Coaches and Players: From a motivational standpoint, the findings support the idea that salary spreads can align with effort incentives. However, cohesion must still be managed. While inequality itself is not toxic, the fairness of how those salaries are earned still matters. Players are more likely to accept pay gaps if they perceive them as earned and performance driven. This reinforces the importance of role clarity, merit-based rotations, and internal transparency within teams. Additionally, teams that limit inactive turnover, or avoiding constant roster reshuffles, may maintain better chemistry and continuity, indirectly improving performance.

Owners and Executives: For ownership, the findings validate spending, but not blindly. Payroll increases lead to better performance, but only when that money reaches active, healthy players. Luxury tax spending, when tied to active contributors, improves outcomes. But overspending on injured or benched players reduces returns. Strategic investment, especially in high availability stars, provides more value than simply having the highest payroll.

League Officials and CBA Designers: At the league level, the study highlights how roster rules shape team incentives. If the NBA aims to promote league-wide competitiveness while sustaining a high level of on-court intensity, then maintaining flexibility in how teams allocate payroll matters. Two-way contracts and injury exceptions can soften the blow of unavailable players by allowing teams to temporarily replace sidelined players without severely disrupting cap structure or team depth. This may improve league-wide efficiency by ensuring that salary resources are more consistently tied to available contributors and by minimizing the competitive decline associated with injuries or roster constraints. Policies that reduce the prevalence or impact of retained salary, buyouts, or dead cap may also help align financial inputs with on-court output. However, the motivations behind these policies are not purely economic. League officials and collective bargaining agreement (CBA) designers often operate under competing incentives. Owners may push for provisions that limit long-term financial exposure, seeking downside protection for high-risk contracts, while players advocate for security in the form of guaranteed money and longer contract horizons, especially in a league where a single injury can derail a career. These structural tensions reflect deeper disagreements about how risk should be shared across the labor-management relationship. Players often emphasize the human element of professional sports, where careers can be fragile, while owners focus on controlling downside and asset protection. The result is a system where how inequality is delivered, whether it feels earned or imposed, can matter as much as the inequality itself. If league rules promote inequality without regard to fairness, clarity, or player wellbeing, they risk amplifying the toxic elements of disparity, even if the empirical models suggest tournament-style incentives work on average. Policymakers must be mindful that the structure of inequality matters, and that trust, stability, and health infrastructure are critical to ensuring that economic incentives produce their intended results.

Contributions to the Literature: This paper moves the conversation forward in several ways. First, it reinforces the value of looking only at active salaries, clarifying that the inequality-performance link is strongest when focused on current contributors. Second, it introduces a composite outcome metric that better reflects team value than win-loss percentage alone. Third, it brings in instrumental variables to understand causality and tests an interaction hypothesis is commonly inferred. Finally, it ties all findings back to economic theory, balancing tournament and fairness models in an applied context.

In summary, inequality, when focused on those who play, can improve performance, but that performance is contingent on health, depth, and organizational alignment. The optimal team is not necessarily the most equal or most expensive, but the most efficient in converting payroll into performance. That is the key lesson for anyone building, managing, or governing in the modern NBA.

Conclusion and Future Directions

In this paper, how intra-team salary inequality affects NBA team performance is examined using a panel dataset covering all 30 franchises from the 2017 to 2023 seasons. The composite performance metric that multiplies Adjusted Net Rating and team-summed VORP is constructed, each rescaled to a 0 to 1 interval. This captures both team efficiency and cumulative player value. To measure inequality, Gini coefficient is used calculated exclusively from active-player salaries. This isolates the incentive effects of pay dispersion among contributors and avoids confounding from unproductive salary categories like dead or retained contracts.

The findings consistently support tournament theory. Across ordinary least squares, fixed effects, instrumental variable regressions, and ordered probit models, greater pay dispersion among active players is associated with improved team performance. This relationship remains strong even after controlling for payroll size, luxury tax status, team valuation, and injury-related salary share. When inequality is measured across all salary types, including inactive contracts, the positive association disappears. This distinction confirms that only pay structures tied to current contributors influence performance in a meaningful way.

Injury-related salary share is a strong and consistent negative predictor of team performance. Teams with a larger portion of payroll tied up in injured players perform worse, regardless of total spending. These results emphasize that the benefits of inequality depend on player availability. The incentive effects that drive performance under tournament theory break down when significant salary resources are allocated to sidelined players. Additionally, interaction models show that top-heavy rosters are not uniquely vulnerable to injury risk. The overall injury burden, not which players are affected, drives the performance decline.

Instrumental variable models strengthen the causal interpretation. By using lagged salary cap levels and prior payroll as instruments for Active Gini, concerns about reverse causality are addressed. In the preferred model specification, higher active-player inequality has a significant positive effect on team performance. However, detecting a nonlinearity through a squared Gini term are inconclusive due to weak instruments. While this limits the ability to test for an optimal level of inequality, the consistent positive effect of the linear term supports the core conclusion.

This study contributes to the literature by developing a more precise inequality measure that focuses on contributors on the court. How the performance metric is constructed reflects how front offices evaluate outcomes with greater context and theoretical link than simple win percentage. By accounting for structural team differences and testing for causal effects, the models offer practical insights grounded in economic theory. The results support a more nuanced view: inequality improves performance when it reflects current effort and contribution, not simply pay scale or roster reputation.

From a managerial perspective, these findings emphasize that pay inequality is not inherently beneficial or harmful. Its effects depend on whether it is perceived as fair, transparent, and aligned with actual contributions on the court. Star-focused payrolls may enhance performance, but only when embedded in an organizational culture that treats players with respect, supports their well-being, and communicates contract decisions clearly. In such environments, inequality can function as a legitimate motivational tool. However, when compensation gaps are viewed as arbitrary or disconnected from effort and impact, they can damage morale and erode team cohesion. The evidence supports a contextual interpretation: pay dispersion improves performance when situated within a system that fosters trust, fairness, and long-term development. Managing payroll structure is not just a financial matter but also a relational one. Teams that invest in player health, recovery systems, and contractual flexibility are more likely to preserve the benefits of strategic inequality while reducing its risks.

Although a wide range of financial and structural variables are controlled for, other important dynamics lie outside the scope of this paper. Elements such as team culture, coaching style, and leadership structure likely influence how inequality is perceived and whether it motivates or demoralizes. These intangible factors are difficult to quantify but matter in practice. Future research could explore these effects more directly or test whether the results differ across markets, team strategies, or stages of team development.

In conclusion, inequality can improve NBA team performance when it is targeted toward the players who matter most. The optimal team is not necessarily the most equal or most expensive, but the one that most efficiently converts payroll into performance. Teams that align compensation with contribution while actively managing injury risk are more likely to translate spending into success. Strategic pay dispersion, when embedded in a fair and supportive organizational system, offers a sustainable path to competitive excellence.

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